To whom and why should I connect? Co-author recommendation based on powerful and similar peers

Rory L.L. Sie*, Hendrik Drachsler,
Marlies Bitter-Rijpkema and Peter Sloep

Open Universiteit,
P.O. Box 2960, 6401 DL Heerlen,
The Netherlands
Email: rory.sie@ou.nl
Email: Hendrik.drachsler@ou.nl
Email: Marlies.bitter@ou.nl
Email: Peter.sloep@ou.nl
*Corresponding author

Abstract: The present paper offers preliminary outcomes of a user study that investigated the acceptance of a recommender system that suggests future co-authors for scientific article writing. The recommendation approach is twofold: network information (betweenness centrality) and author (keyword) similarity are used to compute the utility of peers in a network of co-authors. Two sets of recommendations were provided to the participants: Set one focused on all candidate authors, including co-authors of a target user to strengthen current bonds and strive for acceptance of a certain research topic. Set two focused on solely new co-authors of a target user to foster creativity, excluding current co-authors. A small-scale evaluation suggests that the utility-based recommendation approach is promising, but to maximise outcome, we need to (a) compensate for researchers' interests that change over time and (b) account for multi-person co-authored papers.

Keywords: research; cooperation; network; similarity; recommender systems; utility-based; utility; betweenness centrality.

Reference to this paper should be made as follows: Sie, R.L.L., Drachsler, H., Bitter-Rijpkema, M. and Sloep, P. (2012) 'To whom and why should I connect? Co-author recommendation based on powerful and similar peers', *Int. J. Technology Enhanced Learning*, Vol. 4, Nos. 1/2, pp.121–137.

Bibliographical notes: Rory L.L. Sie is a PhD candidate in the Open Universiteit, The Netherlands. He served as chair and founder of the PhD council of the Open Universiteit in the Netherlands and chair of the PhD council of national research school SIKS. His main focus is on cooperation networks and how we can use social network analysis and game theoretic solution concepts to foster successful cooperation. In a more general sense, he is interested in how we can apply techniques from artificial intelligence (multi-agent systems, intelligent virtual agents, semantic web) to education and learning.

Hendrik Drachsler has more than 20 publications in the field of Technology-Enhanced Learning and he serves as reviewer and programme committee member for international conferences, workshops, and journals. In his current

work, he focuses on the personalisation of information with information retrieval technologies and recommender systems. Furthermore, he is interested on research on educational datasets, linked data, learning networks, data mashups, data visualisations and learning analytics. Next to these activities he steers the Special Interest Group dataTEL of the European Association of TEL and organises an annual workshops series for relevant research topics like the SIRTEL08, SIRTEL09, RecSysTEL2010, dataTEL11.

Marlies Bitter-Rijpkema works as Assistant Professor at CELSTEC/OUNL. Her research focuses on creative problem solving and knowledge building in virtual communities. Over the years, she worked in various roles in (inter)national (EU-FP7) projects (recently idSpace) and operated as liaison officer for the Dutch Digital University Consortium, accelerating TEL educational innovation in higher education. As educational technologist she realised various e-learning solutions (f.e. virtual business simulations, community based thesis writing). Currently her research focuses on knowledge support for collaborative creativity, inventive problem solving in distributed teams, self-organised learning in innovation networks and business modelling for open education.

Peter Sloep is full Professor in Technology Enhanced Learning at CELSTEC, OUNL and programme director of its R&D programme on Networked Learning. His research encompasses such topics as learning design, learning objects and open educational resources, as well as knowledge sharing and creative collaboration in communities and networks. He serves on the editorial board of Research in Learning Technology, frequently reviews papers and book proposals for various journals and conferences in the TEL field, and has reviewed proposals for the Canadian, US and Dutch national research agencies. He supervises several doctoral students.

1 Introduction

Both innovation and organisational change suffer from similar problems. One of the main reasons organisational change fails is the lack of a guiding coalition (Kotter, 1996). To successfully change an organisation, it is important that several powerful employees adopt a change. Innovation implementation often fails because the innovation does not fit the values of the employees (Klein and Sorra, 1996). Thus, both experience a lack of support and commitment. For example, the Post-It note was not perceived as valuable by the 3M company until the employee that came up with the idea started spreading the notes among secretaries. The secretaries kept asking for more of these notes, which eventually persuaded the Marketing and Strategy department (West, 2002); a guiding coalition was formed by the inventor and the secretaries.

The solution to effective change and innovation implementation seems obvious. We have to find the right, powerful peers to connect to. Please note that by powerful, we do not mean powerful by hierarchy per se. Powerful peers can be think-alike, for example, people that have the ability to persuade others or senior employees. Though, a number of problems hinder one from finding the right peers. Firstly, people face an abundance of other people that they can connect to (information overload (Choudhury et al., 2008)). Secondly, people are *boundedly rational* (Simon, 1991; Selten, 1998); they lack the cognitive abilities to determine the value of candidate cooperating peers, also due to *lack of awareness* (Reinhardt et al., 2011b). Thirdly, people are self-interested (Kau and Rubin, 1979; Ratner and Miller, 2001); they need an incentive for cooperation. In other words, they need to know what the added value is of cooperating with others. Indeed, other people hold complementary knowledge. Therefore, many recommender approaches nowadays focus on recommendation of peers to discover complementary knowledge (Vassileva et al., 2003; Beham et al., 2010).

We argue that the above problems result in non-optimal outcomes in research collaboration. In this study, we investigate a co-authorship network in order to recommend possible future cooperative writings. Other studies acknowledge the same problems in research and try to solve them by raising awareness (Reinhardt et al., 2011b), designing a platform to mediate collaboration (Ullmann et al., 2010) or recommending scientific events (Klamma et al., 2009). The overall aims of this system are to (a) raise awareness about possible co-authors in one's network; (b) promote collaboration with other researchers and (c) increase effectiveness and efficiency of collaboration.

Our approach is inspired by two thoughts: (a) networked innovation and learning and (b) utility theory. With respect to the first thought, we regard cooperative writing of research papers (network interactions) as a joint learning and innovation action. By cooperatively writing a paper, the authors necessarily connect to each other. Together, the authors (nodes) and paper writing (edges) form a network of co-authors.

With respect to the second thought, we use the prospective value (utility) of candidate cooperation to recommend peers. Expected utility calculations originate from game theory. It widely gained popularity when John von Neumann and Oscar Morgenstern published their book *Theory of Games and Economic Behaviour* back in 1945 (Neumann and Morgenstern, 1945). As the title suggests, it was initially used for the analysis and prediction of economic behaviour. Over the last decades, however, other fields of research have applied game theory, including computer science (Klusch and Gerber, 2002; Abdallah and lesser, 2004; Jonker et al., 2007; Sie et al., 2010). In short, the prospective value of a peer is computed by the network position of a peer and the similarity to that peer in terms of the keywords that they use.

To this end, we extract metadata from a publication database that uses the dspace software. Dspace is a publication database in which researchers can upload their publications. Especially for researchers, it is important to reach out beyond the borders of their own university, connect to other researchers and gain general acceptance through citation of their work. Dspace is based on the Open Archives Initiative (OAI), and offers a predefined, structured method for publishing to and openly extracting metadata from the database. The database at hand consists of a set of presentations, research papers and project deliverables. As noted earlier, the authors of the documents form a network of co–authors and keywords that are provided during submission of the document to the database are used to compute similarity between authors in terms of research interest.

Two sets of recommendations will be shown to the participants. Recommendation Set includes people that the target user has written with so far and recommendation Set 2 excludes these people. The main question we ask ourselves is: *How well do participants perceive a recommendation that is based on keyword similarity and network information to be?* More formally, we think that recommendation Set 1 will be rated higher than recommendation Set 2. This results in the following hypotheses:

H_0: The results of the two recommendation sets are equal.

H_1: The results of recommendation set 1 are higher than the results of recommendation set 2.

The outline of this paper is as follows. In Section 2, we discuss the research methodology. We describe the dataset that we apply, the recommendation algorithm and the method of evaluation. Section 3 presents the results of our evaluation. In Section 4, we discuss the results of the evaluation and in Section 5 we draw our conclusions and provide an outlook for future work.

2 Method

2.1 Data collection

The dataset that we use is extracted from a dspace publication database. The database comprises 1009 research publications, 518 presentations and 357 project deliverables. Submissions were uploaded by approximately 150 employees (authors) of the university that hosts the database. In total, 1174 distinct authors and co-authors – both inter- and intra-university collaborations – have written on a submission in the database. Every submission is placed in a certain category, that is, the department where it was written. Table 1 provides a numerical overview of the database. As for this dataset, which is from a single university, some of the departments do not have a long history of research publications. For example, departments A, B and C have been doing research for over ten years, whereas department D was founded in 2008. Department F and G started doing research in 2004. Differences in the amount of data may influence the resulting recommendations.

Table 1 Numerical overview of the publication database.

Department	*Publications*	*Presentations*	*Deliverables*
A	373	247	184
B	280	170	131
C	155	10	0
D	62	89	42
E	3	2	n/a
F	102	n/a	n/a
G	13	0	n/a
H	43	n/a	n/a
I	21	1	n/a
Totals	1009	519	357

The following metadata is provided by the author when an individual submission is posted to the database.

- Creators: the authors.
- Descriptions: APA reference, sponsors.
- Language.

- Title.
- Subjects: keywords that specify the contents.
- Type: Journal paper, conference paper, book chapter, etc.

Besides, the system automatically saves the following metadata for each submission:

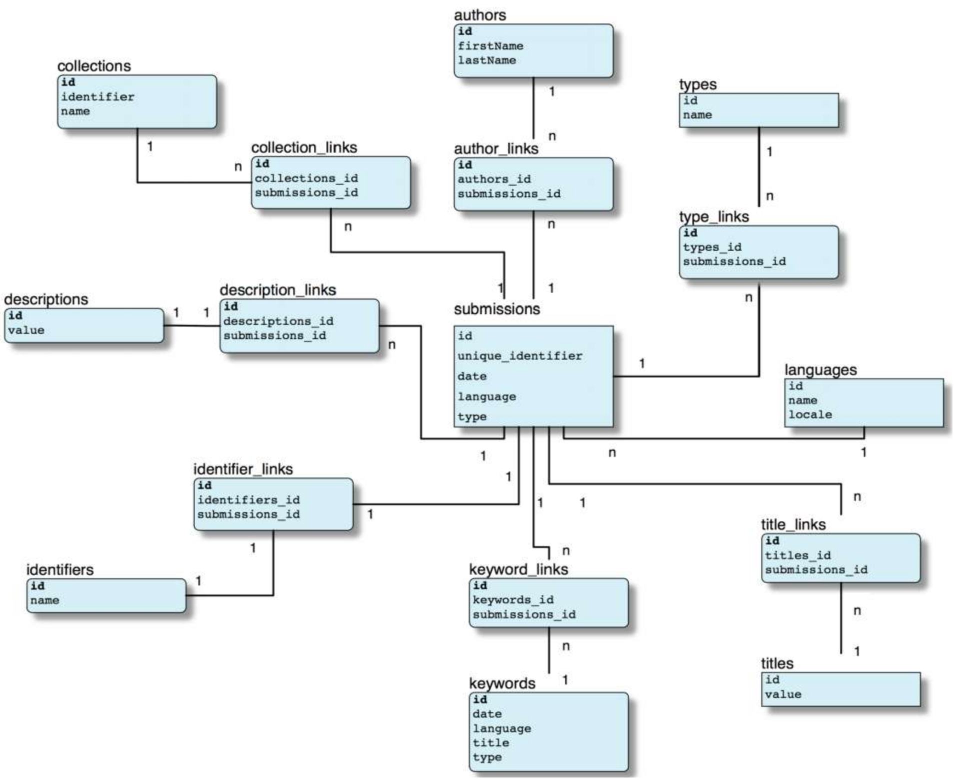
- Unique identifier.
- Timestamp: date and time of submission.

Every submission contains one or more authors. By cooperatively writing an article, the authors are inherently interconnected. These connections can be used to form a so-called *one-mode complete network* of co-authors. This is, however, different than the usual citation networks in which citations between articles are used to generate a network. Besides, we can construct other types of networks to enhance our algorithm, such as relationships based on the department the article was written, the type of submission or the keywords that are used to describe the article. For the present study, we focus on the keywords to measure similarity between authors, but we are planning to further optimise performance by putting the other alternatives to use as well.

The extraction of authors is done as follows. The dspace software is based on the OAI (Lagoze and Van de Sompel, 2001). The OAI provides a protocol for metadata harvesting (OAI-PMH) that can be used to extract submissions from the dspace website. A HTTP request is made to the dspace's OAI-PMH target containing the identifier of a subset (collection) of dspace. The dspace OAI-PMH target returns an XML file that contains all submissions in that subset of the dspace website. Apart from the metadata provided in the XML file, we had no access to any relational model of the dspace database itself. Next, this XML file is read out by a PHP script that splits every entry (submission) into several types of data that are each stored in separate tables in a MySQL database. This repeated for every collection of submissions in dspace. The MySQL database model is shown in Figure 1.

Figure 1 shows that authors and submissions are stored separately. Authors can link (author_links) to multiple submissions, as they store multiple submissions. Submissions can link (author_links) to several authors, as multiple authors can contribute to a single submission. In other words, the co-authors are stored in this database in a so-called 'two-mode' manner. That is, the authors have a connection to a certain submission, and that submission also links to other authors. Though, the authors are not linked themselves. For instance, author A is linked to submission 1 via edge {A, 1} and submission 1 is linked to author B via edge {B, 1}, but there is no edge {A, B} between author A and B. Thus, to create a one-mode co-authorship network in which authors A and B receive a direct link, we should transform the two-mode network to a one-mode network. We do so by performing the following actions: (a) get an author's submissions by retrieving all author links to submissions; (b) for each submission, look for all author links to other authors; (c) save this as a network connection and (d) repeat Step a–c for every author in the database, while keeping in mind not to process duplicates. The approach is similar to that by Breiger (1974), who multiplies the two-mode matrix A (person–object) by its transposed version A^T (object–person) to obtain the person–person matrix $A_1 = AA^T$.

Figure 1 MySQL database model for the dspace data (see online version for colours)



2.2 Recommender system

We envisage the workflow of our recommender system as follows:

1 Co-authors are extracted from papers to create a co-author network.

2 Authors receive a value based on the weighted average of their betweenness centrality and their similarity to the query author.

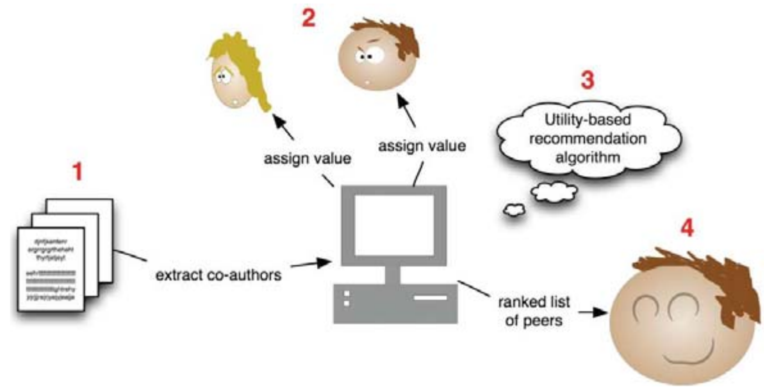
3 Candidate dyadic[1] connections utility-based value.

4 The users receive a ranked list of researchers.

Figure 2 depicts the recommendation process. Numbers correspond to the above list.

After data collection in Step 1 of the workflow, in Step 2 the authors receive a value based on the network position of the authors. To be more precise, betweennesss centrality (Brandes, 1994) is used to calculate to what extent other authors are dependent on an author in terms of information flow. In formal terms, betweenness centrality stands for the number of times a node (author) is on the shortest path of any pair of nodes relative to the total number of shortest paths in the network. In case of co-authorship networks, betweenness centrality stands for the extent to which other authors are dependent of a certain author when disseminating research ideas within the network.

Figure 2 Recommender system workflow (see online version for colours)

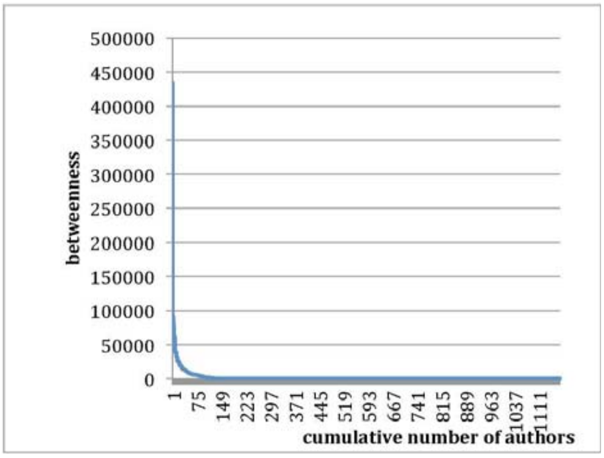


Individuals that have high betweenness centrality in the network are found to be more powerful (Simon, 1982; Krackhardt, 1990; Ibarra, 1992; Ibarra, 1993; Perry-Smith, 2006). In a co-authorship network, we can explain this in two ways: First, individuals that are often on the edge of two networks (high betweenness centrality) have more access to new viewpoints. Therefore, they are able to apply knowledge from one domain to another domain, thereby being more creative (Burt, 2004). Second, individuals that are on the edge of two networks have power over the information flow between the two networks. This gives them more status and power (Krackhardt, 1990). This often shows from an individual's hierarchical position in the organisation in relation to their betweenness centrality. Preliminary observation of our dataset shows that individuals that are high in the organisational hierarchy also have a high betweenness centrality. This leads us to believe there is a relation between key job positions and the betweenness centrality of an individual in an organisation. The betweenness is spread like a *long tail* distribution; few authors have high betweenness and many authors have low betweenness (see Figure 3). Particularly, one person in this graph is responsible for over 80% of the area of the distribution. Less than 1% of the authors (11) are responsible for 50% of the area of the distribution.

Next, we compute the similarity between authors. High similarity, in gender for instance is found to be an indicator for good relationships (Ibarra, 1992), and this is supported by research on homophily and friendships (Lazarsfeld and Merton, 1954; McPherson et al., 2001). To measure similarity, we first have to identify individuals within the network. For each of the authors, we look at their submissions and the keywords that they have used in these submissions.

We prefer to use the keywords over the title or the contents. Akin to this paper's title, authors sometimes use appealing sentences to trigger a potential reader's attention. As a result, mapping the title to the interests of the authors may not always work like we want to. For instance, the paper title 'Birds of a feather:...,' inspired by the proverb 'Birds of a feather flock together', is used to denote that homophily is positively associated with friendships (McPherson et al., 2001). Though, for a computer it is hard to filter out the proverb, as it does not have general knowledge about proverbs and recognising them, and if it did, it should keep a list of all English proverbs. In other words, 'incorrect' titles may distort the automatic semantic interpretation of the title. Processing the full content of papers often takes too much time, especially when the database size increases, and can therefore not be used to compute real-time recommendations. The keywords that authors use to identify their paper are in our opinion the best way to determine their interest and expertise and compute real-time recommendations. Another option would be to pre-process the full content of the papers and only process new entries (submissions) to the system. In general, an indexing mechanism could be used to reduce processing time.

Figure 3 Betweenness centrality of authors, sorted from high to low betweenness (see online version for colours)



Another problem is that authors and keywords need to be disambiguated. For instance, there may be authors that have the same name, for instance, "Michel Klein". Also, female authors may or may not include their maiden name when submitting an article to the dspace database. Moreover, the keywords can be spelled in many ways, such as 'IMS LD' or 'IMS-LD' or 'IMS Learning Design'. As of now, the system does not cope with this, but several similarity measures can be used to deal with this, such as Google similarity (Cilibrasi and Vitanyi, 2007) or perhaps we could use the Wordnet (http://wordnet.princeton.edu/) data set to identify synonyms in keyword use.

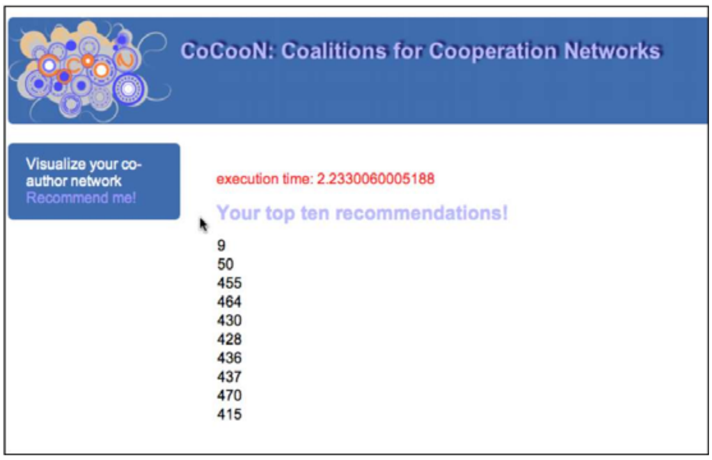
We use the overlap of expertise (keywords) between individuals to express their similarity. In detail, this is done by retrieving the keywords for every paper an author has written. These keywords per author are then used to compute the Term Frequency Inverse Document Frequency (TFIDF). That is, each keyword receives a value, but keywords that are used often receive a lower value. For instance, since a large group of people in our data set work in the field of technology-enhanced learning, the term technology-enhanced learning shows up very often as a keyword in papers. Our recommender system will take this keyword into account, but it receives a lower value because it appears often. In this way, we can recommend more unique co-authors, rather than recommending one author (that used the keyword technology-enhanced learning very often) to everyone. Afterwards, the vector similarity between authors is computed by treating the set of keywords per author as a vector.

A main advantage of TFIDF is frequently used keywords receive a lower value, is at the same time a disadvantage. That is, when someone has a plan to write a general paper about, for instance, the current developments in technology-enhanced learning, that person will not be linked to other people that have used the keyword 'technology-enhanced learning'. One option would be to define an author-keyword matrix B, and multiply this with the transposed keyword-author matrix B^T to gain a keyword-keyword co-occurrence matrix $B_2 = B^T B$. Furthermore, to discover latent relationships between keywords, we can use Latent Semantic Analysis. The disadvantage of the latter is, however, that it is computationally intensive.

In Step 3, we use a utility-based algorithm for our recommendation of peers. The algorithm uses the predictive value of a peer in the network to estimate whether or not cooperation should be pursued. This value is estimated using the two types of similarity from Step 2. However, the two similarities are different in magnitude. For this experiment, we want them to be nearly equal, that is, we want their maximum value to be equal. The maximum betweenness for this dataset is near 400,000 and the maximum keyword similarity is one. To compensate for this, we use a logarithmic scale for the betweenness centrality of authors. Please note that, as for now, we want the two types of similarities to be equal, but this may change after evaluation of the algorithm. Also, future dyadic connections are considered, rather than multi-person cooperation. Doing so influences the way we compute the value of future cooperation. We will go into detail about this in the future work section.

In Step 4, the user receives a ranked list of peers in the network. We distinguish between two types of recommendations. That is, we can include or exclude existing co-authors in the recommendation. If the user chooses not to include existing co-authors, the user receives a list of only new candidate co-authors. We explicitly distinguish between these types of recommendations, as sometimes, people may prefer to write a new paper with existing co-authors rather than new co-authors, due to for instance, trust or time and location constraints. Users are presented a welcome screen, which asks for the author's first and last name and whether or not the author wishes to include existing co-authors. In the future, the author should be able to add a list of keywords that express the topic of the paper to be. In that case, the recommender system should be able to generate co-authors that are even more close to the new paper's goal and topic. Figure 4 shows an example of the resulting recommendation. The execution time was not a performance criterion at this stage. We will add some of our thoughts on this in the future work section.

Figure 4 Example of the co-author recommendation. The candidate co-authors, denoted by numbers, are anonymised (see online version for colours)



For clarification purposes, Table 2 provides a more formal representation of our algorithm, without going into too much detail about the computation of measures such as TFIDF and vector similarity.

Table 2 Recommendation algorithm

Algorithm 2: Co-author recommendation based on betweenness centrality and keyword similarity

```
// create an empty stack for all peers in the network
W ← empty list;
// create empty stack of keywords
K[w] ← empty stack;
// create empty stack of TFIDF values per keyword and author
TFIDF[k,w] ← empty stack;
// create empty stack of vector similarity values for peers
VecSim[w], w ∈ W ← empty stack;
// create empty stack of utility values for peers
U[w], w ∈ W ← empty stack;
// extract all co-authors (see Table 2)
W ← extract coAuthors;
// create empty stack of peer's betweenness centrality
Cb[w] ← empty stack;
foreach peer w ∈ W do
    // save betweenness centrality
    push betweenness centrality of w → Cb[w];
    foreach submission s ∈ S do
        K[w] ← extract keywords;
        foreach keyword k ∈ K[w] do
            push compute TFIDF → TFIDF[k,w];
        end
    end
    push compute vector similarity to w → VecSim[w];
    push compute utility for w → U[w];
end
// sort the peers and their utility from high to low
sort U[w];
// repeat recommendation ten times
counter ← 0;
for counter < 10 do
    // recommend the peer
    recommendation = pop U[w];
    counter++;
end
```

2.3 Evaluation procedure

For the evaluation of the algorithm, we choose to conduct a pilot study. Since this is a first and immature version of the recommendation engine, we aim to investigate the feasibility and identify possible improvements. We do not want involve all potential participants from the sample (approximately 150 people), as they cannot be used for a later, large-scale evaluation due to prior experience with the system. Therefore, we contacted 15 participants to evaluate the two types of recommendation. The participants were selected based on their familiarity with the system, to make sure they understood what the proposed system was about. Therefore, we selected participants from the most active department (A) of this data set. They were invited by email and were addressed personally. A total of ten participants responded positively. No inducement was offered for participation.

Each of the 15 participants received two sets of ten personal recommendations of future co-authors, sorted from high to low ‘utility’. Set 1 was based on all authors that are present in the data set. That is, we include the authors that the user has already written a paper with. This allows one to strengthen current ties in the network. However, some types of creativity are stimulated by connecting to new networks or communities (Burt, 2004). Therefore, Set 2 solely consists of new future co-authors, people that the user has not yet written an article with.

For every co-author that was recommended, the participants had to assign a number ranging from 1 (bad) to 10 (good) to indicate the value of the recommendation. Further clarification said that our recommendation was based on (a) a person that has similar research interests and (b) someone that has persuasive power, due to their occupation or network position. Thus, a ‘good’ recommendation should at least satisfy these two measures.

3 Results

Table 3 shows the results of the evaluation when current co-authors were included in the set of recommended future co-authors. The overall median is 7, which shows that the participants are in general quite positive towards the set of recommendations. As expected, the scores for the individual recommendations R1–R10 gradually decrease, except for R8. Though, R8 shows an increase in score, but also high deviation.

Table 3 Results of the evaluation of recommendation Set 1, when current co-authors were included

Recommendation	*n*	*Mdn*	*SD*
Overall	10	7	2.68
R1	10	8.5	2.9
R2	10	8.5	1.5
R3	10	7	1.6
R4	10	7	1.7
R5	10	6.5	2.4
R6	10	5.5	3.2
R7	10	6.5	3.1
R8	10	8.5	3.3
R9	10	7	2.9
R10	10	6.5	2.9

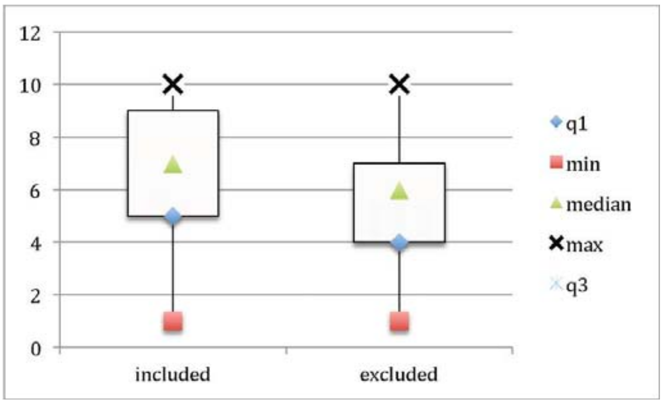
Table 4 shows the results of the evaluation when current co-authors were excluded from the set of recommended future co-authors. The overall median is 6, which shows that the participants are in general quite neutral towards the set of recommendations. The scores for the individual recommendations R1–R10 do not show a clear increase or decrease.

Table 4 Results of the evaluation of recommendation Set 2, when current co-authors were excluded

Recommendation	*n*	*Mdn*	*SD*
Overall	10	6	2.68
R1	10	6	2.4
R2	10	5.5	2.1
R3	10	5	2.5
R4	10	7	2.3
R5	10	6.5	2.3
R6	10	7.5	2.9
R7	10	6	2.5
R8	9	6	3.6
R9	10	4	2.9
R10	10	4.5	2.8

Figure 5 shows a boxplot of the two recommendation sets in general. It shows that recommendation Set 1 (included) score slightly higher. Also, it shows that the responses for recommendation Set 1 skew towards the higher end (max) of the results, whereas the results for recommendation Set 2 are more neutral. Thus, hypothesis H_1 is accepted, whereas the Mann–Whitney–Wilcoxon test shows that H_0 is rejected (Sig. = .016).

Figure 5 Boxplots of the two recommendation sets' results (see online version for colours)



In response to the recommendation we sent, we received some statements from the participants.

Statement 1 "Nothing really new, I also miss people I have obviously an *overlap with like X, Y, Z, S, etc.*." This focuses on the functionality of the algorithm, stating that its recall may be insufficient or that precision and recall may be unbalanced.

Statement 2 "*I don't know him*". This point to a lack of information provided by the system, or a lack of awareness of the user.

Statement 3 "Some people I don't know, and others I do know, bat I don't *know what they do*". This points to a lack of information provided by the system, or a lack of awareness of the user.

Statement 4 "*He is now not active in research bat has done work in the area I work in*". This points to lack of information within the system about active and inactive researchers.

Statement 5 "*He is now not very active in research*". This points to lack of information within the system about active and inactive researchers.

Statement 6 "*His research is now a bit different, games*". This points to user's preferences shifting in focus over time.

4 Discussion

In general, the results of this first test of our algorithm suggest that the participants are neutral to moderately positive about the recommendations that were generated. This leads us to believe that we are on the right track of combining network information with author similarity measures to recommend future co-authors.

The responses of the participants for Set 2 suggest that they are quite neutral toward the recommendations. Analysis of the responses shows that recommendations that are too distant from the target participant are regarded as pointless (Statements 2 and 3). For example, one participant rated four out of ten recommendations with a one, accompanied by the comment "I don't know him". This may point to lack of awareness, as observed earlier in collaborative workspaces (Dourish and Bellotti, 1992; Reinhardt et al., 2011a).

We may investigate how the participants rate recommendation of such 'distant persons' when they are presented how these people are linked to them, that is, the keywords that they have in common. In other words, explaining the workings of the recommender system may improve the user's perception (Sinha and Swearingen, 2002; Herlocker et al., 2004). Also, putting emphasis on the difference between the two sets of recommendations (Set 1 for strengthening bonds and Set 2 for creativity) may help in the adoption of recommendations.

The results for Set 1 indicate that participants are moderately positive about the recommendations of people that they already wrote a paper with. Though, some of the participants' comments indicate that the recommended people were not active in research anymore or that the recommended person shifted focus over time (Statements 4, 5 and 6). We could have gained higher ratings for this set of recommendations if we had compensated for changing preferences. Similar to "time-based discounting of ratings to account for drift in user interests" (Burke, 2002), we may perform time-based discounting of keyword-to-author relatedness.

4.1 Limitations

We need to take into account a number of limitations. First, we did not compensate for any misspelled author names or keywords. Sometimes, when people enter the names of their co-authors of their publication, they misspell the name, leading to two entries that point to the same person. To solve this, we would either have to compute the lexical similarity between a co-author's name and the misspelled version of that co-author's name, such as the Google similarity distance (Cilibrasi and Vitanyi, 2007) between them. Another option would be to manually search the database for any entries that are misspelled and save them in a thesaurus.

Second, people's preferences can change over time. So can researchers' interests. Throughout their scientific career, researchers often work in several universities or institutes, thereby inherently changing their focus, even if they keep working in the same research area. As a result of changing research interests, the keywords that researchers provided in publications from 2004 may be totally different than the keywords that they use in recent publications.

Third, this follows partly from the previous point, time may influence our recommendation in another way. Researchers do not always stay in the same field of research, but may show up in recommendations based on their past publications. They may have even left research to work in business or due to retirement. This severely influences the quality of our recommendations, as we will see in the results section. We will include this in future work.

5 Conclusion

In the present article we investigated how participants perceived utility-based recommendations of future co-authors. Expected utility originates from game theory and is especially useful to determine the expected value of a strategy, in this case a future co-authored paper. The main research question we asked ourselves was: *How well do participants perceive a recommendation that is based on keyword similarity and network information to be?* A small-scale evaluation was performed to determine the feasibility and receive intermediate feedback before we proceed with further development and a large-scale study. Neutral to moderately positive results indicate that the combination of network information (betweenness) and keyword similarity to recommend future co-authors is promising, but needs some improvements to maximise its potential.

The authors envisage three main points of improvement to the current recommender system. First, the current recommender system suggests dyadic connections, whereas co-authored papers often include more than two individuals. The current algorithm is well suited to replace the dyad-based concept of utility by a solution concept that focuses on multi-person cooperation. We propose the use of coalition theory in general and particularly the application of the Shapley value (Shapley, 1953; Hart, 1987) and the nucleolus (Schmeidler, 1969; Kohlberg, 1971) to value candidate cooperation partners, as noted by Sie et al. (2010).

Secondly, we wish to account for drift in the users' research interests. Research interests change over time and we need to compensate for this. Akin to Billsus and Pazzani (2000) and Pazzani (1999) that accounted for drift in user preferences, we need to give lower weight to keywords that were assigned to papers further back in time.

Thirdly, we wish to expand the dataset by including data from Mendeley (mendeley.com) and other dspace publication databases, which are also freely accessible. This allows us to complete our network of candidate co-authors and compute network information more precisely.

Apart from the improvements stated above, we plan to improve the performance of the system. We can do so by pre-processing the graph of authors and graph calculations and process submissions as they are entered into the system. Also, the database could be transformed into a semantic database. The new version of SPARQL (a query language) allows for the querying of property paths, such as the links between co-authors. Besides it allows for a maximum search depth, which may improve the performance of the system as well. Finally, the database could be optimised by an indexing mechanism.

Keyword similarity performance may be improved by extending the set of keywords in our database by extracting keywords from open databases such as DBpedia. The main advantage would not have to process each new keyword and its distance to existing keywords over and over again, as the new keyword already exists in the database.

The next step in our research is to refine the system according to at least the above improvements. Furthermore, we aim to perform a large-scale evaluation of the recommender system.

References

Abdallah, S. and Lesser, V. (2004) 'Organization-based cooperative coalition formation', *Proceedings of the IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT2004)*, 20–24 September, Beijing, China, pp.162–168.

Beham, G., Kump, B., Ley, T. and Lindstaedt, S. (2010) 'Recommending knowledgeable people in a work-integrated learning system', *Procedia Computer Science*, Vol. 1, No. 2, pp.2783–2792.

Billsus, D. and Pazzani, M.J. (2000) 'User modeling for adaptive news access', *User Modeling and User-Adapted Interaction*, Vol. 10, Nos. 2/3, pp.147–180.

Brandes, U. (1994) 'A faster algorithm for betweenness centrality', *Journal of Mathematical Sociology*, Vol. 25, No. 2, pp.163–177.

Breiger, R.L. (1974) 'The duality of persons and groups', *Social Forces*, Vol. 53, No. 2, pp.181–190.

Burke, R. (2002) 'Hybrid recommender systems: survey and experiments', *User Modeling and User-Adapted Interaction*, Vol. 12, No. 4, pp.331–370.

Burt, R.S. (2004) 'Structural holes and good ideas', *American Journal of Sociology*, Vol. 110, No. 2, pp.349–399.

Cilibrasi, R. and Vitanyi, P. (2007) 'The Google similarity distance', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 19, No. 3, pp.370–383.

Choudhury, M.D., Sundaram, H., John, A. and Seligmann, D. (2008) 'Dynamic prediction of communication flow using social context', *Proceedings of the 19th ACM conference on Hypertext and Hypermedia – HT'08*, 19–21 June, Pittsburgh, PA, USA, pp.49–54.

Dourish, P. and Bellotti, V. (1992) 'Awareness and coordination in shared workspaces', *Proceedings of the 1992 ACM Conference on Computer-Supported Cooperative Work – CSCW '92*, 31 October–4 November, Toronto, Canada, pp.107–114.

Hart, S. (1987) 'Shapley value', *The New Palgrave*, pp.318–320.

Herlocker, J.L., Konstan, J.A. Terveen, L.G. and Riedl, J.T. (2004) 'Evaluating collaborative filtering recommender systems', *ACM Transactions on Information Systems*, Vol. 22, No. 1, pp.5–53.

Ibarra, H. (1992) 'Homophily and differential returns: sex differences in network structure and access in an advertising firm', *Science*, Vol. 37, No. 3, pp.422–447.

Ibarra, H. (1993) 'Network centrality, power, and innovation involvement: determinants of technical and administrative roles', *Academy of Management Journal*, Vol. 36, No. 3, pp.471–501.

Jonker, C.M., Robu, V. and Treur, J. (2007) 'An agent architecture for multi-attribute negotiation using incomplete preference information', *Autonomous Agents and Multi-Agent Systems*, Vol. 15, No. 2, pp.221–252.

Kau, J.B. and Rubin, P.H. (1979) 'Self-interest, ideology, and logrolling in congressional voting', *Journal of Law and Economics*, Vol. 22, No. 2, pp.365–384.

Klamma, R., Phnam, M.C. and Cao, Y. (2009) 'You never walk alone: recommending academic events based on social network analysis', *Complex Sciences*, Vol. 4, No. 1, pp.657–670.

Klein, K.J. and Sorra, J.S. (1996) 'The challenge of innovation implementation', *Academy of Management Review*, Vol. 21, No. 4, pp.1055–1080.

Klusch, M. and Gerber, A. (2002) 'Dynamic coalition formation among rational agents', *IEEE Intelligent Systems*, Vol. 17, No. 3, pp.42–47.

Kohlberg, E. (1971) 'On the nucleolus of a characteristic function game', *SIAM Journal on Applied Mathematics*, Vol. 20, No. 1, pp.62–66.

Kotter, J.P. (1996) *Leading Change*, Harvard Business Press, p.208.

Krackhardt, D. (1990) 'Assessing the political landscape: structure, cognition, and power in organizations', *Administrative Science Quarterly*, Vol. 35, No. 2, pp.342–369.

Lagoze, C. and Van de Sompel, H. (2001) 'The open archives initiative: building a low-barrier interoperability framework', *Russian Digital Libraries Journal*, Vol. 4, No. 6.

Lazarsfeld, P.F. and Merton, R.K. (1954) 'Friendship as a social process: a substantive and methodological analysis', in Berger, M., Abel, T. and Page, C.H. (Eds): *Freedom and Control in Modern Society*, Van Nostrand, Vol. 18, pp.18–66.

McPherson, M., Smith-Lovin, L. and Cook, J.M. (2001) 'Birds of a feather: homophily in social networks', *Annual Review of Sociology*, Vol. 27, No. 1, pp.415–444.

Neumann, J.V. and Morgenstern, O. (1945) 'Theory of games and economic behavior', *Bulletin of the American Mathematical Society*, Vol. 51, pp.498–504.

Pazzani, M.J. (1999) 'A framework for collaborative, content-based and demographic filtering', *Artificial Intelligence Review*, Vol. 13, No. 5, pp.393–408.

Perry-Smith, J. (2006) 'Social yet creative: the role of social relationships in facilitating individual creativity', *Academy of Management Journal*, Vol. 49, No. 1, pp.85–101.

Ratner, R.K. and Miller, D.T. (2001) 'The norm of self-interest and its effects on social action', *Journal of personality and social psychology*, Vol. 81, No. 1, pp.5–16.

Reinhardt, W., Meier, C., Drachsler, H. and Sloep, P. (2011a) 'Analyzing 5 years of EC-TEL proceedings', in Kloos, C.D., Gillet, D., Garcia, R.M.C., Wild, F. and Wolpers, M. (Eds): *Towards Ubiquitous Learning – Proceedings of the 6th European Conference on Technology Enhanced Learning*, 20–23 September, Palermo, Italy, pp.531–536.

Reinhardt, W., Mletzko, C., Drachsler, H. and Sloep, P. (2011b) 'AWESOME: a widget-based dashboard for awareness-support in research networks', *Proceedings of the 2nd Conference on Personal Learning Environments (PLE)*, 10–12 July, Southampton, UK.

Schmeidler, D. (1969) 'The nucleolus of a characteristic function game', *SIAM Journal on Applied Mathematics*, Vol. 17, No. 6, pp.1163–1170.

Selten, R. (1998) 'Features of experimentally observed bounded rationality', *European Economic Review*, Vol. 42, pp.413–436.

Shapley, L.S. (1953) 'A value for n-person games. Contribution to the theory of games', in Kuhn, H.W. and Tucker, A.W. (Eds): *Annals of Mathematics Studies*, Vol. 2, p.28.

Sie, R.L.L., Bitter-Rijpkema, M. and Sloep, P.B. (2010). 'A simulation for content-based and utility-based recommendation of candidate coalitions in virtual creativity teams', *Procedia Computer Science: RecSysTEL2010*, Vol. 1, No. 2, pp.2883–2888.

Simon, H.A. (1982) *Models of Bounded Rationality*, MIT Press.

Simon, H.A. (1991) 'Bounded rationality and organizational learning', *Organization Science*, Vol. 2, No. 1, pp.125–134.

Sinha, R. and Swearingen, K. (2002) 'The role of transparency in recommender systems', *CHI'02 Extended Abstracts on Human Factors in Computing Systems – CHI'02*, 20–25 April, Minneapolis, MN, USA, pp.830–831.

Ullmann, T.D., Fridolin, W., Scott, P., Duval, E., Vandeputte, B., Parra, C., Gonzalo, A., Reinhardt, W., Heinze, N., Kraker, P., Fessl, A., Lindstaedt, S., Nagel, T. and Gillet, D. (2010) 'Components of a research 2.0 infrastructure', in Dimitrova, V., Wolpers, M. and Kirschner, P. (Eds): *Proceedings of the 5th European Conference on Technology-Enhanced Learning (ECTEL'10)*, 28 September–1 October, Barcelona, Spain, pp.590–595.

Vassileva, J., McCalla, G. and Greer, J. (2003) 'Multi-agent multi-user modeling in I-help', *User Modeling and User-Adapted Interaction*, Vol. 13, No. 1, pp.179–210.

West, M.A. (2002) 'Sparkling fountains or stagnant ponds: an integrative model of creativity and innovation implementation in work groups', *Applied Psychology: An International Review*, Vol. 51, No. 3, pp.355–424.

Note

1 A dyad is another name for two people that belong to the same social group, in this example candidate co-authors.